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EXAMINER	
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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No.	Applicant(s)	
	10/590,397	CHEN, YURONG	
	Examiner	Art Unit	
	Brian E. Weinrich	2169	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE *3* MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *26 July 2010*.

2a)☒ This action is **FINAL**. 2b)☐ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-11,13-21,23-29 and 31-33* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-10,13-17,19-21,23-28 and 31-33* is/are rejected.

7)☒ Claim(s) *11,18 and 29* is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *21 August 2006* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☒ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☒ All b)☐ Some * c)☐ None of:

1.☒ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date *April 11, 2008*.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

DETAILED ACTION

Remarks

1. In response to communications filed on July 26, 2010, claims 7, 8, 19, 21, 23-27 and 29 have been amended, claims 31-33 added and claims 12, 22 and 30 cancelled at the applicant's request. Amended claims 7, 8, 19, 21, 23-27 and 29 and claims 1-6, 9-11, 13-18, 20, 28 and 31-33 are presented for examination.

Claim Objections

2. Claims 32 and 33 are objected to because of the following informalities: it appears that line 8, claim 32, which concludes "said GMM including a plurality of Gaussian components," should end with a comma (,) rather than a period (.). It appears that the limitation paragraph of lines 9 and 10, claim 32, which concludes "to produce a preliminary similarity measure," should end with a comma (,) rather than a semicolon (;). In line 5, claim 33, it appears that there should not be an "and" at the end of the line. It appears that the limitation paragraph of lines 6 and 7, claim 33, which concludes "a Gaussian Mixture model of said target audio clip," should end with a comma (,) rather than a semicolon (;). It appears that the antecedent basis of the recitations of "the segment" and "said segment" in claims 32 and 33 is the segment in "for each segment" and not in "at least one segment." Appropriate correction is required.

Claim Rejections - 35 USC § 103

3. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

4. Amended claims 7, 8, 19, 21, 23-27 and 29 and claims 1-6, 9-11, 13-18, 20, 28, 31 and 33 are rejected under 35 U.S.C. 103(a) as being unpatentable over Cunningham (US 2002/0129038) in view of Attias (US 2004/0002935) and Cereghini et al. (Cereghini) (US 6,496,834).

a. Referring to claim 1:

i. Cunningham teaches a method for searching a database for a target clip (computer implemented data mining using Gaussian Mixture models for data accessed from a database in lines 1-6, Abstract) in a multiprocessor system (for relational distributed data mining using parallelism mechanisms in Figure 1, paragraph [0006], page 1 and lines 6-10, paragraph [0032], page 2), comprising:

1st. partitioning said database into a plurality of groups (clustering algorithms that partition the data set of a large database into several disjoint groups, each representing a fraction of the entire database in lines 3 and 4, paragraph [0015], page 1, paragraph [0016], page 1 and lines 1-3, paragraph [0043], page 3);

2nd. establishing a model for said target clip (creating the Gaussian Mixture Model for the accessed data with a Client 114 that provides a user interface for generating SQL statements that retrieve data from a database in paragraph [0029], page 2 and lines 2-6, paragraph [0017], page 1) (See also paragraphs [0030] and [0031], page 2); and

3rd. processing said scheduled groups in parallel by said plurality of processors to search for said target clip (performing operations by the data servers 110 that use partitioning methods with parallelism mechanisms against the relational database in a parallel manner in

which the Expectation-Maximization algorithm of claim 1 is performed iteratively while focusing on the case where there are different clusters in an architecture for relational distributed data mining in paragraph [0006], page 1, lines 6-11, paragraph [0032], page 2, lines 3-6, paragraph [0043], page 3 and claim 2, page 8).

ii. Cunningham does not teach that the database is an audio database and the target clip is an audio clip.

iii. On the other hand, Attias teaches that the database is an audio database and the target clip is an audio clip (databases that are multimedia databases having video or audio clips with the posterior probability that a given segment is the target of a user's search is computed and conditioned on the query segment, the query conditioned on that segment being their target in paragraph [0005], page 1 and lines 3-9, paragraph [0060], page 4).

iv. Cunningham at least suggests dynamically scheduling said plurality of groups to a plurality of processors in said multiprocessor system (scheduling and prioritizing the SQL statements received from the OLAP Client 114 and performing the SQL statements against a Data Mining View 128 to retrieve the data from the database in lines 1-8, paragraph [0030], page 2 and paragraph [0031], page 2); and

v. Moreover, Cereghini teaches dynamically scheduling said plurality of groups (launching several UPDATE statements in parallel and executing queries in parallel in lines 6-8, column 11 and lines 5 and 6, column 12) to a plurality of processors in said multiprocessor system (in a massively parallel processing environment or MPP computer system 200 comprised of one or more nodes 202, each of the nodes 202 comprised of one or more processors in Figure 2 and lines 46-52, column 4).

vi. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

vii. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

b. Referring to claim 2:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 1.

ii. Cunningham and Attias do not teach *the method of searching an audio database for a target audio clip in a multiprocessor system*, wherein partitioning said audio database comprises determining a size for each of said plurality of groups, said size being determined to reduce the amount of overlapped computation among said plurality of groups and load imbalance in parallel processing of said plurality of groups.

iii. On the other hand, Cereghini teaches wherein partitioning said audio database comprises determining a size for each of said plurality of groups, said size being determined to reduce the amount of overlapped computation among said plurality of groups and load imbalance in parallel processing of said plurality of groups (executing queries in parallel, speeding-up the

process by making data block size smaller to get a finer grain for parallelism and a better balance load among processors in lines 59-63, column 12).

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips of Attias and with the executing of queries in parallel and data block sizes in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases of Attias and the executing of queries in parallel and data block sizes of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

c. Referring to claim 3: Cunningham teaches *the method of searching an audio database for a target audio clip in a multiprocessor system*, wherein establishing a model for said target audio clip comprises extracting a feature vector sequence from said target audio clip and modeling said feature vector sequence (the Expectation-Maximization or EM algorithm generalizing the probability density function to get the multivariate normal density for a p-dimensional vector in paragraph [0036], page 2 and paragraph [0038], page 3) based on a Gaussian Mixture model ("GMM") (the EM algorithm performed to create the Gaussian Mixture Model for the accessed data in lines 2-6, paragraph [0017], page 1), said GMM including a

plurality of Gaussian components (fitted by a linear combination of Gaussian or normal distributions in paragraph [0036], page 2).

d. Referring to claim 4: Cunningham teaches *the method of searching an audio database for a target audio clip in a multiprocessor system (3) with extraction and modeling of a feature vector sequence*, wherein modeling said feature vector sequence comprises estimating mixture weights for each of said plurality of Gaussian components (the likelihood that the mixture of multivariate normal distributions for p-dimensional vectors is given by the formula $p(x) = \sum w_i\, p(x,i)$ where $p(x,i)$ is the normal probability density function for each cluster and w_i is the weight that cluster represents from the entire database in paragraph [0038], pages 2 and 3, paragraph [0042], page 3 and lines 1-3, paragraph [0043], page 3) (See also lines 9-12, paragraph [0047], page 3).

e. Referring to claim 5:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 1.

ii. Cunningham at least suggests *the method of searching an audio database for a target audio clip in a multiprocessor system*, wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (distinguishing segments in the accessed data in claim 13, page 8) (See also paragraphs [0097]-[0100], page 5); and

2nd. for each segment,

(01) extracting a feature vector sequence for the segment (each cluster having its corresponding vector in lines 3-6, paragraph [0043], page 3), and

(02) modeling said feature vector sequence (the Expectation-Maximization or EM algorithm generalizing the probability density function to get the multivariate normal density for a p-dimensional vector in paragraph [0036], page 2 and paragraph [0038], page 3) based on a Gaussian Mixture model ("GMM") (the EM algorithm performed to create the Gaussian Mixture Model for the accessed data in lines 2-6, paragraph [0017], page 1), said GMM including a plurality of Gaussian components (fitted by a linear combination of Gaussian or normal distributions in paragraph [0036], page 2).

iii. Furthermore, Attias teaches wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (generating segment profiles of at least one segment of each file being searched, the files clustered based, at least in part, upon vector quantization of the extracted features in Figures 5 and 6, lines 6 and 7, paragraph [0065], page 4 and lines 1-4, paragraph [0068], page 5); and (If a segment belongs to a file of a cluster, then the segment also belongs to the cluster.)

2nd. for each segment,

(01) extracting a feature vector sequence for the segment (extracting features from subband signals which are extracted from segments of files in Figure 5, lines 3-6, paragraph [0065], page 4), and

(02) modeling said feature vector sequence based on a Gaussian Mixture model ("GMM"), said GMM including a plurality of Gaussian components (fitting a Gaussian mixture model to the extracted subband signals for each frame based, at least in part, upon responsibility of mixture components of the mixture model in paragraph [0066], pages 4 and 5).

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

f. Referring to claim 6:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 5.

ii. Cunningham and Cereghini do not teach *the method of searching an audio database for a target audio clip in a multiprocessor system (5) with feature vector sequences extracted and modeled for segments of scheduled groups*, wherein each of said at least one segment has the same length in time as that of said target audio clip.

iii. On the other hand, Attias teaches wherein each of said at least one segment has the same length in time as that of said target audio clip (the query segment can be, for example, a segment of audio such as a song or particular voice that a user desires to find within the multi-media files, the system generating segment profiles of segments to provide information associated with a likelihood that a particular file of the multi-media files includes the query

segment based, at least in part, upon the query profile and a segment profile of the particular file in lines 6-11, paragraph [0012], page 1 and in lines 2-5, paragraph [0046], page 3).

(The query segment and the segment of audio ... that a user desires of Attias correspond to the target audio clip of the application and the at least one segment. Since the query segment and the segment of audio ... that a user desires are the same, they must have the same length.)

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

g. Referring to amended claim 7:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 5.

ii. Cunningham and Cereghini do not teach *the method of searching an audio database for a target audio clip in a multiprocessor system (5) with feature vector sequences extracted and modeled for segments of scheduled groups*, wherein if there is more than one

segment in an audio stream, each segment partially overlaps with a segment that immediately precedes that segment.

iii. Attias teaches wherein if there is more than one segment in an audio stream, each segment partially overlaps with a segment that immediately precedes that segment (the segment profile for a segment is based on responsibility vectors of the frames of the segment from which subband signals are extracted which are obtained by applying an N-point window to frames of the files in lines 3-6 paragraph [0033], page 2, lines 3-8, paragraph [0064], page 4 and lines 1-4, paragraph [0068], page 5).

(The concept of using a window to extract subband signals from frames within segments means some of the frames in one segment in the window will be the same as some of the frames in the next segment from which subband signals are extracted. Such a window would advance one frame at a time as it extracts subband signals for segments.)

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining)

in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

h. Referring to amended claim 8:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 5. Furthermore, Cunningham teaches *the method of searching an audio database for a target audio clip in a multiprocessor system (5) with feature vector sequences extracted and modeled for segments of scheduled groups*, wherein (a) said plurality of Gaussian components are common for different segments and said target audio clip (the mixture of multivariate normal distributions for p-dimensional vectors focuses on the case where each cluster has their corresponding vector and all of them have the same covariance matrix E in lines 1-3, paragraph [0042], page 3 and lines 3-6, paragraph [0043], page 3) and

ii. Cunningham at least suggests wherein (b) said different segments include equivalent mean and variance values (The mean of the distribution is μ and its variance is σ^2, the samples from variables having this distribution tending to form clusters around the mean μ with the points scattered around the mean measured by σ^2 in lines 2-5, paragraph [0037], page 2) (See also Table 2, page 3).

iii. Furthermore, Attias teaches wherein (b) said different segments include equivalent mean and variance values (the model has S components labeled s = 1 . . . , S which are Gaussian with mean μ_s, a prior distribution on the segment and a probability defined as the exponential of the KL distance between the query and the segment and modified by a term determining the variance of that probability in paragraphs [0037] and [0038], page 3 and lines 5-12, paragraph [0060], page 4).

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

i. Referring to claim 9: Cunningham teaches *the method of searching an audio database for a target audio clip in a multiprocessor system (5) with feature vector sequences extracted and modeled for segments of scheduled groups (8) and common Gaussian components*, wherein modeling said feature vector sequence comprises estimating mixture weights for each of said plurality of Gaussian components (the likelihood that the mixture of multivariate normal distributions for p-dimensional vectors is given by the formula $p(x) = \sum w_i \, p(x,i)$ where $p(x,i)$ is the normal probability density function for each cluster and w_i is the weight that cluster represents from the entire database in paragraph [0038], pages 2 and 3, paragraph [0042], page 3 and lines 1-3, paragraph [0043], page 3) (See also lines 9-12, paragraph [0047], page 3).

j. Referring to claim 10:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 9.

ii. Cunningham and Cereghini do not teach *the method of searching an audio database for a target audio clip in a multiprocessor system (5) with feature vector sequences extracted and modeled for segments of scheduled groups (8) and common Gaussian components (9) with modeling by the mixture of multivariate normal distributions*, further comprising: for each segment,

1st. computing a Kullback-Leibler ("KL") distance between a GMM of said segment and a GMM of said target audio clip; and

2nd. determining that said segment matches said target audio clip, if said KL distance is smaller than a pre-determined threshold.

iii. However, Cunningham teaches for each segment, determining that said segment matches said target audio clip, if the log likelihood is smaller than a pre-determined threshold (executing the E step and the M step in the Expectation-Maximization or EM algorithm as long as the change in log-likelihood or llh is greater than ε in paragraph [0050], page 3) (See also Figure 2A and paragraphs [0051], [0055] and [0056], pages 3 and 4).

(If Cunningham can keep an algorithm executing as long as the log-likelihood is greater than ε, it is obvious that it could do so using the Kullback-Leibler ("KL") distance.)

iv. On the other hand, Attias teaches for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4), computing a Kullback-Leibler ("KL") distance between a GMM of said segment and a GMM of said target audio clip (calculating a Kullback-Leibler or KL distance between the query profile q_s generated based on a query segment and the segment

profile r_s in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4) (See also paragraphs [0053] and [0054], page 4); and

v. Moreover, Attias at least suggests for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4), determining that said segment matches said target audio clip, if said KL distance is smaller than a pre-determined threshold (providing information associated with a likelihood such as a probability, by implementing the KL distance, that a particular file includes the query segment based, at least in part, upon the query profile and a segment profile of a segment of the particular file in paragraphs [0053] and [0054], page 4).

vi. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that terminate using a tolerance that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments with the computation of Kullback-Leibler (KL) distance of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

vii. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms with tolerance of Cunningham with the multimedia databases and generated segments and Kullback-Leibler (KL) distance of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database. Furthermore, the Kullback-Leibler (KL) distance

of Attias is a likelihood similar to the log-likelihood of Cunningham which is compared to a tolerance.

k. Referring to claim 31:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 3.

ii. Cunningham at least suggests *the method of searching an audio database for a target audio clip in a multiprocessor system (3) with extraction and modeling of a feature vector sequence*, wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (distinguishing segments in the accessed data in claim 13, page 8) (See also paragraphs [0097]-[0100], page 5); and

2nd. for each segment,

(01) extracting a feature vector sequence for the segment (each cluster having its corresponding vector in lines 3-6, paragraph [0043], page 3), and

(02) modeling said feature vector sequence (the Expectation-Maximization or EM algorithm generalizing the probability density function to get the multivariate normal density for a p-dimensional vector in paragraph [0036], page 2 and paragraph [0038], page 3) based on a Gaussian Mixture model ("GMM") (the EM algorithm performed to create the Gaussian Mixture Model for the accessed data in lines 2-6, paragraph [0017], page 1), said GMM including a plurality of Gaussian components (fitted by a linear combination of Gaussian or normal distributions in paragraph [0036], page 2).

iii. Furthermore, Attias teaches wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (generating segment profiles of at least one segment of each file being searched, the files clustered based, at least in part, upon vector quantization of the extracted features in Figures 5 and 6, lines 6 and 7, paragraph [0065], page 4 and lines 1-4, paragraph [0068], page 5); and (If a segment belongs to a file of a cluster, then the segment also belongs to the cluster.)

2nd. for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4),

(01) extracting a feature vector sequence for the segment (extracting features from subband signals which are extracted from segments of files in Figure 5, lines 3-6, paragraph [0065], page 4), and

(02) modeling said feature vector sequence based on a Gaussian Mixture model ("GMM"), said GMM including a plurality of Gaussian components (fitting a Gaussian mixture model to the extracted subband signals for each frame based, at least in part, upon responsibility of mixture components of the mixture model in paragraph [0066], pages 4 and 5).

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and

Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

l. Referring to claim 33:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 1.

ii. Cunningham and Cereghini do not teach *the method of searching an audio database for a target audio clip in a multiprocessor system*, wherein processing said scheduled groups in parallel comprises:

1st. for each segment,

(01) extracting a feature vector sequence for the segment (each cluster having its corresponding vector in lines 3-6, paragraph [0043], page 3),

(02) computing a Kullback-Leibler ("KL") distance directly between the feature vector sequence for the segment and a Gaussian Mixture model of said target audio clip.

iii. However, Cunningham teaches wherein processing said scheduled groups in parallel comprises:

1st. for each segment,

(01) determining that said segment matches said target audio clip, if the log-likelihood is smaller than a pre-determined threshold (executing the E step and the M step in the Expectation-Maximization or EM algorithm as long as the change in log-likelihood or llh is greater than ε in paragraph [0050], page 3) (See also Figure 2A and paragraphs [0051], [0055] and [0056], pages 3 and 4).

(If Cunningham can keep an algorithm executing as long as the log-likelihood is greater than ε, it is obvious that it could do so using the Kullback-Leibler ("KL") distance.)

iv. Cunningham at least suggests wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (distinguishing segments in the accessed data in claim 13, page 8) (See also paragraphs [0097]-[0100], page 5); and

2nd. for each segment,

(01) extracting a feature vector sequence for the segment (each cluster having its corresponding vector in lines 3-6, paragraph [0043], page 3).

v. Furthermore, Attias teaches wherein processing said scheduled groups in parallel comprises:

1st. partitioning each of said scheduled groups into at least one segment (generating segment profiles of at least one segment of each file being searched, the files clustered based, at least in part, upon vector quantization of the extracted features in Figures 5 and 6, lines 6 and 7, paragraph [0065], page 4 and lines 1-4, paragraph [0068], page 5); and (If a segment belongs to a file of a cluster, then the segment also belongs to the cluster.);

2nd. for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4),

(01) extracting a feature vector sequence for the segment (extracting features from subband signals which are extracted from segments of files in Figure 5, lines 3-6, paragraph [0065], page 4), and

(02) computing a Kullback-Leibler ("KL") distance directly between the feature vector sequence for the segment and a Gaussian Mixture model of said target audio clip (calculating a Kullback-Leibler or KL distance between the query profile q_s generated based on a query segment and the segment profile r_s in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4) (See also paragraphs [0053] and [0054], page 4).

vi. Moreover, Attias at least suggests

1st. for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4),

(01) determining that said segment matches said target audio clip, if said KL distance is smaller than a pre-determined threshold (providing information associated with a likelihood such as a probability, by implementing the KL distance, that a particular file includes the query segment based, at least in part, upon the query profile and a segment profile of a segment of the particular file in paragraphs [0053] and [0054], page 4).

vii. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that terminate using a tolerance that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments and the computation of Kullback-Leibler (KL) distance of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

viii. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms with tolerance of Cunningham with the multimedia databases, generated segments and Kullback-Leibler (KL) distance of Attias and the executing of queries in

parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database. Furthermore, the Kullback-Leibler (KL) distance of Attias is a likelihood similar to the log-likelihood of Cunningham which is compared to a tolerance.

m. Referring to claims 13-17: Claims 13 and 14 are directed to a similar scope as claims 1 and 2 respectively except for the limitations of a partitioning module, a scheduler and an audio search model. Cunningham teaches a partitioning module (a server 106 in Figure 1 and paragraph [0031], page 2) and an audio search model (the RDBMS 132 interfaced to the data servers 110A-110E in Figure 1 and lines 1-3, paragraph [0032], page 2) when combined with Attias (databases that are multimedia databases having video or audio clips in paragraph [0005], page 1) and Cereghini teaches a scheduler (computer programs on the nodes 202 in Figure 1 and lines 56-67, column 4). Therefore, claims 13 and 14 are rejected with the same rationale applied against claims 1 and 2 respectively. Furthermore, claim 15 is directed to a scope within the scope of claims 5, 6 and 8 except for the limitations of a feature extractor and a modeling module. Attias teaches a feature extractor (a feature extractor 120 in Figure 1 and lines 3-6, paragraph [0031], page 2 and paragraph [0034], page 3) and a modeling module (a query component 210 in Figure 2 and paragraphs [0046] and [0047], page 3). Finally, claim 16 is directed to a scope within the scope of claims 5 and 8 and claim 17 is directed to a similar scope as claim 10. Therefore, claim 16 is rejected with the same rationale applied against claims 5 and 8 and claim 17 is rejected with the same rationale applied against claim 10.

n. Referring to amended claim 19: Claim 19 is directed to a similar scope as claim 1 except for the limitations that the target audio clip is a predetermined and non-randomly selected and that the processing of said scheduled groups in parallel is after partitioning said audio database into the plurality of groups. Cunningham teaches that

i. the target audio clip is a predetermined and non-randomly selected (the data is retrieved from a database by a Client 114 that provides a user interface for generating SQL statements in paragraph [0029], page 2) (See also paragraphs [0030] and [0031], page 2); and

ii. that the processing of said scheduled groups in parallel is after partitioning said audio database into the plurality of groups (focuses on the case where there are different clusters in an architecture for relational distributed data mining in which the Expectation-Maximization algorithm of claim 1 is performed iteratively in paragraph [0006], page 1, lines 3-6, paragraph [0043], page 3 and claim 2, page 8).

Furthermore, Attias also teaches that

i. the target audio clip is a predetermined and non-randomly selected (audio clips in which the posterior probability that a given segment is the target of a user's search is computed and conditioned on the query segment, the query conditioned on that segment being their target in paragraph [0005], page 1 and lines 3-9, paragraph [0060], page 4).

Therefore, claim 19 is rejected with the same rationale applied against claim 1. Note that the method discussed in claim 1 is implemented by the combination of the software environment of Cunningham (in Figure 1 and paragraph [0028], page 2), the computer components of Attias (in Figure 3 and paragraph [0057], page 4) and computer programs on the nodes 202 of Cereghini

(in Figure 1 and lines 56-67, column 4) which correspond to the instructions that the articles of claim 19 comprise.

o. Referring to amended claim 21: The additional limitations of claim 21 are directed to a similar scope as the additional limitations of claim 3 except for the limitation of wherein the feature vector sequence respectively includes a feature vector for every frame of a plurality of frames included in the target audio clip. Attias teaches wherein the feature vector sequence respectively includes a feature vector for every frame of a plurality of frames included in the target audio clip (the responsibility of each component s of frame n form a responsibility vector for a frame n for substantially all frames in a profile segment of each of the files in paragraphs [0039] and [0040], page 3 and lines 1-3, paragraph [0051], page 4) (See also paragraphs [0009], [0010] and [0014], page 1). Therefore, claim 21 is rejected with the same rationale applied against claim 3. Note that the method discussed in claim 3 is implemented by the combination of the software environment of Cunningham (in Figure 1 and paragraph [0028], page 2), the computer components of Attias (in Figure 3 and paragraph [0057], page 4) and computer programs on the nodes 202 of Cereghini (in Figure 1 and lines 56-67, column 4) which correspond to the instructions that the articles of claim 21 comprise.

p. Referring to amended claim 23: The additional limitations of claim 23 are directed to a similar scope as the additional limitations of claim 5 except for the limitation of wherein the feature vector sequence respectively includes a feature vector for every frame of a plurality of flames included in the segment. Attias teaches wherein the feature vector sequence respectively includes a feature vector for every frame of a plurality of flames included in the segment (the responsibility of each component s of frame n form a responsibility vector for a frame n for

substantially all frames in a profile segment of each of the files in paragraphs [0039] and [0040], page 3 and lines 1-3, paragraph [0051], page 4) (See also paragraphs [0009], [0010] and [0014], page 1). Therefore, claim 23 is rejected with the same rationale applied against claim 5. Note that the method discussed in claim 5 is implemented by the combination of the software environment of Cunningham (in Figure 1 and paragraph [0028], page 2), the computer components of Attias (in Figure 3 and paragraph [0057], page 4) and computer programs on the nodes 202 of Cereghini (in Figure 1 and lines 56-67, column 4) which correspond to the instructions that the articles of claim 23 comprise.

q. Referring to amended claim 24: The additional limitations of claim 24 are directed to a similar scope as the additional limitations of claim 6 except for the limitation of wherein (a) modeling said feature vector sequence comprises estimating mixture weights for each of said plurality of Gaussian components. Cunningham teaches wherein (a) modeling said feature vector sequence comprises estimating mixture weights for each of said plurality of Gaussian components (the likelihood that the mixture of multivariate normal distributions for p-dimensional vectors is given by the formula $p(x) = \sum w_i \, p(x,i)$ where $p(x,i)$ is the normal probability density function for each cluster and w_i is the weight that cluster represents from the entire database in paragraph [0038], pages 2 and 3, paragraph [0042], page 3 and lines 1-3, paragraph [0043], page 3) (See also lines 9-12, paragraph [0047], page 3). Therefore, claim 24 is rejected with the same rationale applied against claim 6. Note that the method discussed in claim 6 is implemented by the combination of the software environment of Cunningham (in Figure 1 and paragraph [0028], page 2), the computer components of Attias (in Figure 3 and paragraph

[0057], page 4) and computer programs on the nodes 202 of Cereghini (in Figure 1 and lines 56-67, column 4) which correspond to the instructions that the articles of claim 24 comprise.

r. Referring to amended claim 27:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 26.

ii. Cunningham at least suggests *the article comprising a machine-readable medium that contains instructions, which when executed by a processing platform, cause said processing platform to perform operations (23) with feature vector sequences extracted and modeled for segments of scheduled groups (26) and common Gaussian components*, wherein modeling said feature vector sequence comprises modeling said feature vector sequence in a non-repetitive and non-cyclical manner (the Expectation-Maximization or EM algorithm performed to create the Gaussian Mixture Model for the accessed data in lines 2-6, paragraph [0017], page 1 fitted by a linear combination of Gaussian or normal distributions in paragraph [0036], page 2).
(There is an embodiment in Cunningham, seen in claim 2, page 8, where the EM algorithm is performed iteratively and therefore is repetitive. Claim 1, page 8, however, gives an embodiment of the EM algorithm is not performed iteratively and, therefore, is not repetitive or cyclical.)

iii. Furthermore, Attias teaches *the article comprising a machine-readable medium that contains instructions, which when executed by a processing platform, cause said processing platform to perform operations (23) with feature vector sequences extracted and modeled for segments of scheduled groups (26) and common Gaussian components*, wherein modeling said feature vector sequence comprises modeling said feature vector sequence in a non-repetitive and

non-cyclical manner (fitting a Gaussian mixture model to the extracted subband signals for each frame based, at least in part, upon responsibility of mixture components of the mixture model in paragraph [0066], pages 4 and 5).

(The examiner cannot find anything that indicates that the fitting of a Gaussian mixture model in paragraph [0066], pages 4 and 5 of Attias is repetitive or cyclical.)

iv. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias and with the executing of queries in parallel in the massively parallel processing environment of Cereghini.

v. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias and the executing of queries in parallel of Cereghini because Cunningham, Attias and Cereghini all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database.

s. Referring to amended claims 25 and 26 and claims 20 and 28: The additional limitations of claims 20, 25, 26 and 28 are directed to a similar scope as the additional limitations of claims 2, 7, 8 and 10 respectively. Therefore, claims 20, 25, 26 and 28 are rejected with the same rationale applied against claims 2, 7, 8 and 10 respectively. Note that the methods discussed in claims 2, 7, 8 and 10 are implemented by the combination of the software environment of Cunningham (in Figure 1 and paragraph [0028], page 2), the computer

components of Attias (in Figure 3 and paragraph [0057], page 4) and computer programs on the nodes 202 of Cereghini (in Figure 1 and lines 56-67, column 4) which correspond to the instructions that the articles of claims 20, 25, 26 and 28 respectively comprise.

5. Claim 32 is rejected under 35 U.S.C. 103(a) as being unpatentable over Cunningham (US 2002/0129038), Attias (US 2004/0002935) and Cereghini et al. (Cereghini) (US 6,496,834) as applied to claim 1 above in view of Wang et al. (Wang) (Yih-Ru Wang and Chen-Yu Chiang. A New Common Component GMM-Based Speaker Recognition Method. In: IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005, Proceedings. (ICASSP '05), pages I-645 – I-648, March 23, 2005).

a. Referring to claim 32:

i. Cunningham, Attias and Cereghini combine to teach all the limitations of claim 1.

ii. Cunningham at least suggests *the method of searching an audio database for a target audio clip in a multiprocessor system*, including:

1st. establishing a first preliminary model for a first and second frame of said target audio clip (creating the Gaussian Mixture Model for the accessed data with a Client 114 that provides a user interface for generating SQL statements that retrieve data from a database in paragraph [0029], page 2 and lines 2-6, paragraph [0017], page 1) (See also paragraphs [0030] and [0031], page 2);

(If Cunningham reads on establishing a model for the target clip, it at least suggests establishing a first preliminary model for a first and second frame of said target audio clip.)

2nd. partitioning each of said scheduled groups into at least one segment (distinguishing segments in the accessed data in claim 13, page 8) (See also paragraphs [0097]-[0100], page 5); and

3rd. for each segment,

(01) extracting a first feature vector sequence for a first and second frame of the segment (each cluster having its corresponding vector in lines 3-6, paragraph [0043], page 3),

(02) establishing a second preliminary model for said first feature vector sequence based on a Gaussian Mixture model ("GMM") (creating a Gaussian Mixture Model using the results returned from the queries in lines 8-12, paragraph [0030], page 2), said GMM including a plurality of Gaussian components (fitted by a linear combination of Gaussian or normal distributions in paragraph [0036], page 2),

(Since there is a Gaussian Mixture Model created for more than one query, two of them can be created. This at least suggests establishing a second preliminary model for said first feature vector sequence based on a Gaussian Mixture model.)

(03) processing said scheduled groups to search for said target audio clip by comparing the first and second preliminary models to produce a preliminary similarity measure (performing the EM algorithm with different numbers of clusters to keep track of the log-likelihood and the total number of parameters, Akaike's Information Criteria or AIC combining these two parameters, wherein the highest AIC is the best model in lines 1-5, paragraph[0111], page 6), and

(04) extracting a second feature vector sequence for every frame of the segment (there are different clusters, each having their corresponding vector in lines 3-6,

paragraph [0043], page 3) and establishing a full model for said second feature vector sequence based on the preliminary similarity measure exceeding a threshold (partitioning the data set into several disjoint groups, such that two points in the same group are similar and points across groups are different according to some similarity criteria in paragraph [0016], page 1).

iii. Furthermore, Attias teaches:

1st. establishing a first preliminary model for a first and second frame of said target audio clip (fitting a mixture model from Subband signals obtained by applying an N-point window to frames of the files in lines 3-6, paragraph [0033], page 2 and lines 4-7, paragraph [0067], page 5);

(If N = 2, then the window in a 2-point window meaning that there are two frames in it. Thus, the first window will comprise the first two frames.)

2nd. partitioning each of said scheduled groups into at least one segment (generating segment profiles of at least one segment of each file being searched, the files clustered based, at least in part, upon vector quantization of the extracted features in Figures 5 and 6, lines 6 and 7, paragraph [0065], page 4 and lines 1-4, paragraph [0068], page 5); and

(If a segment belongs to a file of a cluster, then the segment also belongs to the cluster.);

3rd. for each segment (each of a plurality of generated segment profiles r_s of a segment in lines 4-8, paragraph [0045], page 3 and lines 1-3, paragraph [0055], page 4),

(01) extracting a first feature vector sequence for a first and second frame of the segment (generating a responsibility vector for the frames in Figure 1 and lines 1-4, paragraph [0036]).

(When N = 2 in lines 3-6, paragraph [0033] of Attias, the responsibility vectors are generated for two consecutive frames including the first two frames.)

iv. Moreover, Cereghini teaches:

1st. for each segment,

(01) establishing a second preliminary model for said first feature vector sequence based on a Gaussian Mixture model ("GMM"), said GMM including a plurality of Gaussian components (the Gaussian mixture model probability function in the EM algorithm assumes the data is formed by the mixture of k multivariate normal distributions on p variables. The Gaussian mixture model probability function in lines 35-38, column 6), and

(For a model to be formed using p variables is to be a model for a vector since p variables form a vector.)

(02) processing said scheduled groups to search for said target audio clip by comparing the first and second preliminary models to produce a preliminary similarity measure (The EM clustering algorithm works to estimate the Gaussian mixture probability function by successively improving the solution found so far stopping when the quality of the current solution becomes stable as measured by a monotonically increasing statistical quantity called loglikelihood in lines 51-58, column 6).

(To work by successively improving the solution means that two successive estimates of the Gaussian mixture probability function are compared.)

v. Finally, Wang teaches

(01) extracting a second feature vector sequence for every frame of the segment and establishing a full model for said second feature vector sequence based on the preliminary similarity measure exceeding a threshold (given $\lambda_s' = \{(c_{is}, \mu_{is}, \Sigma)\}; i = 0, \ldots, M - 1\}$, find μ_i of the CCGMM model $\lambda_s = \{(c_{is}, \mu_i, \Sigma)\}; i = 0, \ldots, M - 1\}$ and find the new model $\overline{\lambda_s'} = \{(\overline{c_{is}}, \overline{\mu_{is}}, \overline{\Sigma})\}; i = 0, \ldots, M - 1\}$ in the last paragraph, page I-646 which is in Section 3).

vi. It would have been obvious to a person of ordinary skill in the art at the time the invention was made to have enhanced the clustering algorithms that create Gaussian Mixture models in Cunningham with the multimedia databases containing audio clips and generated segments of Attias, with the executing of queries in parallel in the massively parallel processing environment of Cereghini and with the common component Gaussian Mixture Model (CCGMM) of Wang with its calculation of similarity using divergence.

vii. A person of ordinary skill in the art would have been motivated to combine the clustering algorithms of Cunningham with the multimedia databases and generated segments of Attias, the executing of queries in parallel of Cereghini and the CCGMM of Wang because Cunningham, Attias, Cereghini and Wang all deal with clustering data in databases in the process of searching (i.e., data mining) in multiprocessor systems including the use of Gaussian Mixture models and the ability to use parallel data retrieval for a database does not depend on the type of data in the database. Furthermore, both Attias and Wang deal with audio or speech data stored in databases.

Allowable Subject Matter

6. Claims 11 and 18 and amended claim 29 are objected to as being dependent upon a rejected base claim, but would be allowable if rewritten in independent form including all of the limitations of the base claim and any intervening claims as well as claim 7.

7. The following is a statement of reasons for the indication of allowable subject matter: the effective filing data of the application is July 3, 2006. About nine months after the effective filing data, the applicant co-authored a paper (Yurong Chen, Wei Wei, Yimin Zhang. Parallel Audio Quick Search on Shared-Memory Multiprocessor Systems. http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=04228292. The 8th IEEE International Workshop on Parallel and Distributed Scientific and Engineering (PDSEC-07), Proceedings of 21st International Parallel & Distributed Processing Symposium (IPDPS'07), Long Beach, CA, USA, March 26-30, 2007, 6 pages) that was published in the Proceedings of 21st International Parallel & Distributed Processing Symposium. This symposium was an IEEE symposium. IEEE conferences and symposiums have high quality refereeing so that the reviewers of the papers at this conference would only allow a paper having novel material to be published. IEEE Conferences typically reject 70%-80% of the papers submitted to them. The paper covered many of the same topics as the claims which are indicated as allowable. The novelty in this paper appears to be the application of Gaussian Mixture Models to the parallel processing of searches of an audio database for audio target clips using clustering, overlapping segments, Kullback-Leibler distance and skipping of segments. Section 2 on the first and second pages of the paper appears to indicate that neither the application of Gaussian Mixture Models to searches of an audio database for audio target clips using overlapping segments, Kullback-Leibler

distance and skipping of segments by themselves nor the parallel processing of searches of an audio database for audio target clips using clustering, Kullback-Leibler distance and skipping of segments by themselves are novel. The applicant's paper repeatedly cites the paper (Yih-Ru Wang and Chi-Han Huang. Speaker-and-Environment Change Detection in Broadcast News Using the Common Component GMM-Based Divergence Measure. In: Proceedings of the 8th International Conference on Spoken Language Processing (INTERSPEECH-2004), Jeju Island, Korea, pages 1069-1072, October 4-8, 2004) while indicating what is not novel. Thus, the applicant is aware of the existence of this paper (although it was not in the IDS form PTO-1449). Now, in the office action of April 26, 2010 it seemed to the examiner that the combination of Cunningham, Attias and Cereghini read claims 11, 18 and 29. The examiner, however, is now deferring to the judgment of the reviewers in this IEEE symposium.

8. As allowable subject matter has been indicated, applicant's reply must either comply with all formal requirements or specifically traverse each requirement not complied with. See 37 CFR 1.111(b) and MPEP § 707.07(a).

Response to Arguments

9. Applicant's arguments, filed July 26, 2010, with respect to the rejection of claim 1 (and therefore claim 13) under 35 U.S.C. 103(a) regarding groups have been fully considered, but they are not persuasive. Cunningham clearly teaches that clustering algorithms partition the data set into groups in lines 3 and 4, paragraph [0015], page 1 and paragraph [0016], page 1. Paragraph [0016] clearly says that the groups come from clustering. Thus, there is a clustering into groups disclosed in Cunningham. To cluster data into groups is to derive them.

Cunningham repeatedly refers to clusters in its disclosure. There is, first of all, the clustering in lines 1-3, paragraph [0043], page 3 cited in the context of claim 4 in the office action of April 26, 2010 where Cunningham discloses obtaining the fraction of the database that a cluster represents. The applicant appears to be arguing, however, that when the relational database has operations performed against it (i.e., the things that are processed) by Cunningham in lines 6-11, paragraph [0032], page 2, it is not the groups that Cunningham forms by clustering that are being processed. The remainder of paragraph [0043] (lines 3-6) of Cunningham, also cited in the office action of April 26, 2010, says that "the present invention focuses on the case where there are different clusters." If this is what the invention focuses on, it is difficult to argue that the operations in paragraph [0032] are not performed on the clusters. Moreover, in paragraph [0006], page 1, the invention of Cunningham is for "an architecture for relational distributed data mining." The word distributed is a synonym for the word parallel. Claim 2, page 8 says that the Expectation-Maximization algorithm of claim 1 is performed iteratively. Thus, in iteration 2, the Expectation-Maximization algorithm works with the clusters formed in iteration 1.

10. Applicant's arguments, filed July 26, 2010, with respect to the rejection of claim 1 under 35 U.S.C. 103(a) regarding the target clip have been fully considered, but they are not persuasive. The applicant argues that the accessed data is not the same as target data (or clip). In paragraphs [0029]-[0031], however, Cunningham uses SQL to retrieve (i.e., access) data. The most important part of an SQL statement in the accessing of data is the WHERE clause. In the WHERE clause, one specifies which data to retrieve. Thus, using SQL, the WHERE clause targets data. If the applicant is not convinced, Attias also has a targeted search in lines 3-9,

paragraph [0060], page 4. The rejection of claim 1 (and therefore claim 13) under 35 U.S.C. 103(a) is therefore maintained.

11. Applicant's arguments, filed July 26, 2010, with respect to the rejection of claim 6 under 35 U.S.C. 103(a) have been fully considered, but they are not persuasive. The applicant appears to argue that segments in Attias do not come from partitioning of groups. The mapping of claim 5 in the office action of April 26, 2010 shows that they do. As seen in the office action, in Figures 5 and 6, lines 6 and 7, paragraph [0065], page 4 and lines 1-4, paragraph [0068], page 5, Attias generates segment profiles of at least one segment of each file being searched, the files clustered based, at least in part, upon vector quantization of the extracted features. Since the files belong to clusters, so do the segments. The examiner, however, gave the wrong paragraph while giving the right quotation. It is paragraph [0065], page 4 that reads "the files are clustered based, at least in part, upon vector quantization of the extracted features" in lines 6 and 7 and not paragraph [0067]. Attias indicates more than one time that the segments of its file clusters which it generates are searched in lines 6-11, paragraph [0012], page 1, lines 3-9, paragraph [0060] and lines 1-4, paragraph [0068], page 5, for example. The rejection of claim 6 under 35 U.S.C. 103(a) is therefore maintained.

12. Applicant's arguments, filed July 26, 2010, with respect to the rejection of claim 11 have been fully considered, but they are not persuasive. The response, however, is now irrelevant because the examiner is indicating claim 11 as allowable although for different reasons than those about which the applicant argues.

Conclusion

13. Applicant's amendment necessitated the new ground(s) of rejection presented in this Office action. Accordingly, **THIS ACTION IS MADE FINAL**. See MPEP § 706.07(a). Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the date of this final action.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Brian E. Weinrich whose telephone number is 571-270-3793. The examiner can normally be reached on Monday-Friday 9-5 ET.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Tony Mahmoudi can be reached on 571-272-4078. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free). If you would like assistance from a USPTO Customer Service Representative or access to the automated information system, call 800-786-9199 (IN USA OR CANADA) or 571-272-1000.

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